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MULTI MODAL TRANSPORTATION PATH SELECTION OF COAL BASED ON GENETIC ALGORITHM

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Abstract. In order to solve the problem of selecting transportation routes and transfer nodes reasonably in the process of multimodal logistics distribution, the author proposes a coal transportation multimodal transportation path selection based on genetic algorithm. Firstly, this paper establishes an object function for routing according to the features of multi-modal transport, which has the minimum transport time, the minimum transport length and the minimum transport cost. Secondly, we design appropriate GA components, and get a multiobjective route optimal model for multimodal transport by using GA. Taking into account the high transportation costs of coal as a bulk commodity, a coal transportation multimodal transport path optimization model was constructed with the total transportation cost as the objective function of the model, and the minimum economic cost as the objective. At last, this paper applies GA and MATLAB to resolve the case. Experiments showed that the starting population was 90, with a cross rate of 0.6 and a mutation rate of 0.02. After 100 iterations, it was found that the fitness change between adjacent generations was less than 0.01, indicating that the population mean of the running results had stabilized. At this point, it can be considered that the results have converged. This method validates the practicality of the established model and provides a reference for logistics enterprises to carry out multimodal transportation.

Key words: Multimodal transport, Logistics delivery, Optimize the model, genetic algorithm

1. Introduction. Coal, as the main energy source of the country, currently accounts for nearly 70% of the total energy consumption. According to the current resource composition of the country with "rich coal, poor oil, and little gas", coal as the main energy source for the people will not change significantly in the long term in the future [1]. However, the distribution of coal resources in the country is extremely uneven, with the main production and sales areas of coal separated from each other. This issue has resulted in a transportation pattern characterized by "transporting coal from the north to the south and from the west to the east". Although the country has made many efforts to increase coal transportation capacity, the shortage of transportation capacity is still difficult to fundamentally change in the near future [2,3].

The main energy source of the country is coal, and the stability of coal prices is crucial for the development of the country's industry. Although coal enterprises may increase profits due to the rise in coal prices, other enterprises such as thermal power supply, chemical industry, metallurgy, etc. will experience cost increases due to the rise in coal prices [4]. Therefore, changes in coal prices will have a significant impact on industrial development. The transportation cost of coal is one of the factors affecting coal prices. As transportation costs increase, coal prices will correspondingly rise. In the future, the national coal production will continue to increase, and the main coal mining areas will shift from east to west. The changes in coal mining areas and transportation distances have led to an increase in coal transportation costs, which in turn has driven up coal prices. Therefore, it is urgent to minimize the cost of coal transportation to the greatest extent possible. Coal is a typical bulk commodity that mainly relies on iron wheels for long-distance transportation, and its demand for road transportation is also high. The expansion and renovation of highway and railway facilities have to some extent released the transportation capacity of goods, promoting the use of the shortest path for bulk material transportation, thereby improving transportation efficiency [5]. For example, some of the indirect transportation volume undertaken by sea rail intermodal transport can be returned to direct railway or highway transport, so the optimization of coal transportation multimodal transport routes can be carried

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out while considering the cost of coal transportation and transportation.

The above content is a discussion on the distribution, price, transportation, and other aspects of national coal. Based on this, constructing a national coal multimodal transport network model has certain research significance. But coal is a bulk commodity, and the generalized multimodal transport model will not be suitable for the multimodal transport of coal. Therefore, the author will consider the particularity of coal, construct a multimodal transportation path selection model for coal transportation, combine the characteristics of multiple transportation modes, leverage the overall benefits of multimodal transportation, optimize transportation paths, control transportation costs, improve service efficiency, and create profits for coal enterprises through scientific management methods. At the same time, the author conducted numerical verification and comparative analysis, proving the practicality and feasibility of the research method, providing a certain theoretical basis and work foundation for future related research work [6,7].

2. Literature Review. The reasonable path of multimodal transport refers to a reasonable and feasible transportation route plan that conforms to the characteristics of general cargo owners or multimodal transport operators' cargo transportation operations, including the use of transportation methods. The main body of multimodal transportation is railway, waterway, and air transportation, while road transportation plays a connecting role as the starting and ending points and transit points in the combined transportation path.

Meanwhile, among these modes of transportation with the lowest cost or shortest route, single transportation has lower costs and is more competitive than combined transportation. Therefore, within the reasonable distance range of various transportation modes, transportation companies or freight agents will choose direct transportation to reduce the cost and increase in cargo damage caused by transshipment. Ke, H. et al. developed a model with transportation carbon emissions as the primary objective and freight utility value as a secondary objective. The model adheres to constraints related to overall freight turnover rates, the economic and social benefits of freight transportation, and the ecological limitations of the freight transportation system [8]. Johar et al. analyzed and optimized two parameters of genetic algorithm, namely the generation number and population size. The results indicate that genetic algorithms are effective in maximizing the net present value of supplier payment plans [9]. Jiang et al. developed a multimodal transportation route optimization model aimed at minimizing the total transportation costs, which include transportation, transit, waiting, and carbon emission costs. To solve the model, they use a genetic algorithm incorporating retention and migration strategies. A case study has proven the model's effectiveness and can offer decision support for selecting optimal multimodal transport solutions [10,11].

In summary, existing research mostly constructs multimodal transport path selection and optimization models based on the objective functions of total transportation cost, service level, or optimal transportation time. Generally, these models are transformed into multi-objective combinatorial optimization models, shortest path models, or integer programming models for solution. Analysis shows that most scholars focus on the study of shortest path models, but they often emphasize the arc connections between two points in the network diagram, while ignoring the number of transportation mode conversions and the rationality of the conversion sequence. They mostly achieve optimal paths from a theoretical perspective, but the practical application results are not ideal and cannot achieve the expected goals [12].

3. Method.

3.1. Description of Path Problems. The multimodal transport network includes multiple modes of transportation and transfers between them. Generally, network transformations are used to reasonably represent the transfers between modes of transportation, while also following two principles. First, if there are multiple modes of transportation between two nodes, each mode of transportation corresponds to a separate connection line; Secondly, when there is a transfer operation at a certain node, the transfer of transportation modes is represented by the connecting lines between new nodes, that is, the starting and ending points of each transportation mode are separated, that is, the starting and ending points of each transportation mode are represented by a new node. At transit nodes, the endpoints of various modes of transportation are referred to as inbound nodes, and the starting points of various modes of transportation are referred to as outbound nodes.

The transformed network diagram is shown in Figure 3.1, with two connecting lines added between O-A,

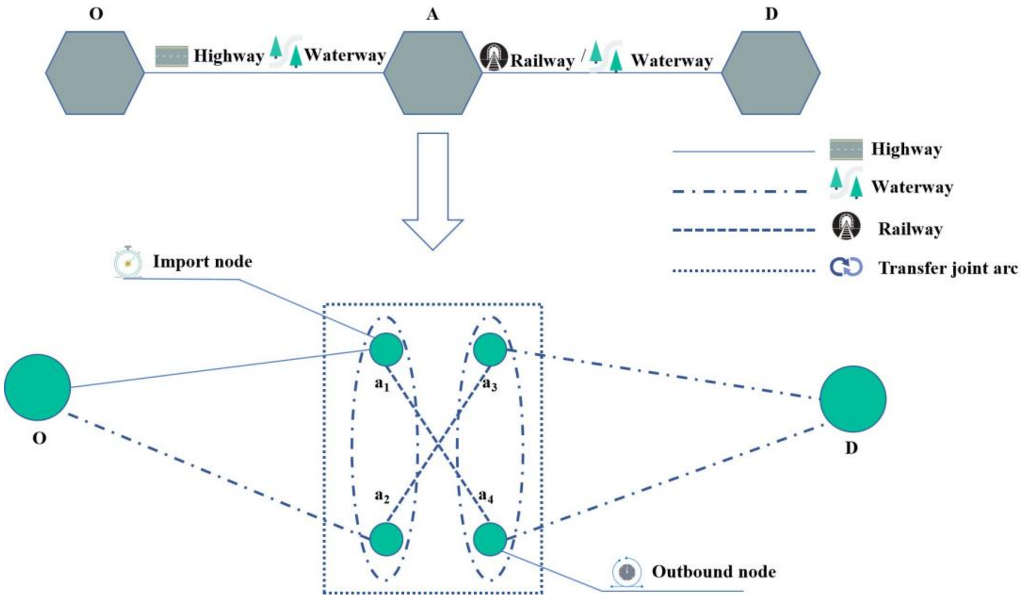

Fig. 3.1: Network Transformation Diagram

representing waterway transportation and highway transportation respectively. Similarly, add two lines between A-D, representing railway transportation and waterway transportation respectively. In addition, there may be a situation of transportation mode transfer at node A, so node A is divided into four nodes $a_1 - a_4$, with each node representing a transportation mode along the lines between O and D [13,14].

We assume the following conditions: (1) There is no increase or decrease in goods during transportation, nor is there any replenishment or reduction of goods; (2) Assuming that the freight demand between ODs is indivisible, meaning that only one mode of transportation can be chosen between two nodes.

3.2. Definition of Model Symbols. Let

E represent the set of all modes of transportation in the multimodal transport network;

N represents the set of all feasible paths;

Q represents the transportation volume of goods;

T represents the delivery time requested by the shipper for the goods, where $T \in [w, v]t$ represents the actual time consumed for the transportation of the goods.

J_t represents the penalty cost per unit time; is the final penalty cost for the goods.

l and m are weight coefficients $\in (0, 1)$ and l+m=1.

$u^e_{n,n+1}$ and $C^e_{n,n+1}$ respectively represent the e-th mode of transportation used between nodes n to n+1 during multimodal transport, as well as the unit transportation cost (yuan/hour/ton) of the e-th mode of transportation.

$b^e_{n,n+1}$ the transportation distance generated between nodes n and n+1 under the e-th mode of transportation.

$R^{eh}_n S^{eh}_n$ respectively represent the transition from the e-th mode of transportation to the h-th mode of transportation and the resulting transit costs during multimodal transport.

$t^e_{n,n+1}$ represents the transportation time for selecting the e-th mode of transportation between nodes n and n+1 during multimodal transport.

$H^e h_n$ represents the transition time from the e-th mode of transportation to the e-th mode of transportation during multimodal transport [15].

3.3. Optimization Model and Constraints. For the convenience of establishing the model, the following assumptions are made.

1. The logistics distribution network of multimodal transportation is fixed and unchanged, and all possible nodes and transportation routes throughout the entire logistics distribution process have been provided;
2. The indicators such as freight rates, transportation time, and transportation capacity of different transportation modes vary among different nodes;
3. Transfer can occur on each node, but each node can only occur once at most. Two nodes can only choose one mode of transportation for goods transportation;
4. The delivery of goods as a whole cannot be divided. During transportation, it is not possible to divide the delivery goods into multiple modes for simultaneous transportation. The transfer of goods can only occur at nodes, not during transportation;
5. Ignoring uncertain factors such as weather changes, road conditions, and human operations throughout the process;
6. The overall logistic cost consists of the transport of goods, the transport of goods, and the penalty. Overall logistic transport time consists of transport time and transport time [16].

Based on the above assumptions, the following logistics distribution path optimization model can be established:

$$\begin{aligned}\min Z = l[(\textstyle\sum_{n\in Ne\in E}\sum_{n,n+1} u^e_{n,n+1}Q) + (\sum_{n\in Ne}\sum_{e\in E} R^{eh}_n S^{eh}_n Q) + J]+ \\ m[\textstyle\sum_{n\in Ne}\sum_{eE} u^e_{n,n+1} + \sum_{n\in Ne}\sum_{e\in E} R^{eh}_n H^{eh}_n Q]\end{aligned} \tag{3.1}$$

The constraint conditions are:

$$\sum_{n\in Ne\in E}\sum_{n,n+1} u_n n + 1 t^e_{n,n+1} + \sum_{n\in N}\sum_{e\in Eh\in E}\sum_{n} R^{eh}_n H^{eh}_n = T \tag{3.2}$$

$$\sum_{n\in Ne\in E}\sum_{n} R^{eh}_n = 1 \tag{3.3}$$

$$u^e_n - 1, n, u^h_{n,n+1} = R^{eh}_n \tag{3.4}$$

$$\sum_{n\in N} u^e_{n,n+1} \leqslant 1 \tag{3.5}$$

$$u^e_{n,n+1}, R^{eh}_n \in \{0,1\} n \in N, e \in E, h \in E \tag{3.6}$$

$$J_t = \left\{ \begin{array}{cc} 0 & t \leqslant v \\ (t-v)z & t \geqslant v \end{array} \right\} \tag{3.7}$$

$$Q \leqslant Q^e_{n,n+1} \tag{3.8}$$

The objective function Z in equation 3.1 is a generalized cost, representing the minimum sum of logistics distribution cost and time cost. Logistics distribution costs are comprised of three components: transportation costs, transit costs, and penalty costs [17]. The total transportation time consists of two parts: the time taken to transport goods while in transit and the time spent at transit nodes;

Equation 3.2 indicates that the total transportation time for goods is equal to the sum of the transit time and the time spent in transit.

Equation 3.3 indicates that if the goods need to be transferred at the transportation node, the transportation mode can only be changed once.

Equation 3.4 represents the continuity of various transportation modes during transportation between two adjacent nodes.

Equation 3.5 represents that in a multimodal logistics network, the transportation mode between two transportation nodes can only be one of road, railway, waterway, and air at most.

Equation 3.6 represents that the decision variable can only take 0 or 1, with 0 indicating that it has not been selected and 1 indicating that it has been selected.

Equation 3.7 represents the penalty cost incurred if the goods cannot be delivered on time according to the time regulations.

Equation 3.8 represents that in the transportation node n to n+1 section, the cargo transportation volume cannot exceed the transportation carrying capacity of the section.

3.4. Genetic Algorithm Steps. There are two main optimization algorithms for logistics transportation and distribution: deterministic algorithms and search algorithms. When encountering some irregular optimization problems, deterministic algorithms cannot accurately search for the optimal solution. Search algorithms are crafted to tackle complex optimization problems by encoding and decoding the issues, aiming to identify the best possible solution. Genetic algorithm is an evolutionary algorithm derived from genetic phenomena in the biological world. Its main feature is that there are no restrictions such as function differentiation and function continuity, and it can process the result object with good global search for optimal solutions [18]. The specific steps of genetic algorithm are as follows.

(1) Initialization. Randomly select an initial population consisting of n chromosomes, with representing this initial population. Use this initial population as the starting point for data iteration to obtain the initial solution.

(2) Choose. Select individuals from the initial population who are more suitable for the environment to reproduce the next generation. According to the fitness calculation method: assuming $f(u_i)$ is the fitness of the selected individual, and P_{ui} is used to represent the probability of chromosome u_i being selected, then there is:

$$P_{ui} = \frac{f(u_i)}{\sum_{i=1}^{n} f(u_i)} \tag{3.9}$$

According to the expression of P_{ui}, it can be seen that the larger the $f(u_i)$ value of an individual, the larger its $f(u_i)$ value, that is, the higher the probability of being selected for inheritance to the next generation. Conversely, the smaller the P_{ui} value of an individual, the smaller its EE value, and the lower the possibility of inheritance to the next generation.

(3) Cross over. Cross operation, also known as recombination operation, selects individuals for breeding the next generation, randomly selects two individuals with the same position, and performs recombination according to the crossover probability p. This biological process represents the random exchange of individual genes, with the aim of generating new gene combinations, that is, producing new individuals. During crossover, crossover operators include single point crossover, multi-point crossover, uniform crossover, etc.

(4) Mutation. The function of mutation operation is to retrieve important genetic information missed by the selection and crossover operations mentioned above. According to the principle of genetic variation in genetics, the mutation probability pm is used to perform mutation operations on genes of individuals containing important genetic information. The emergence of new individuals cannot be achieved through crossover operations, and can only rely on mutation operations [19].

(5) Global harvest. When the $f(u_i)$ value reaches stability, the global optimal harvest is reached, and the algorithm ends. Otherwise, it returns to the selection process and performs a loop operation.

The iterative process of the algorithm concludes when the fitness of the optimal individual meets the specified threshold, or when neither the fitness of the optimal individual nor the overall fitness of the population shows further improvement. If these conditions are not met, the algorithm replaces the current generation with the new population generated through selection, crossover, and mutation, and repeats the process from step 2, continuing the selection operation in a loop.

3.5. Solving Design Based on Genetic Algorithm.

Chromosome coding design. The specific encoding process of genetic computing is as follows: the first gene on the chromosome is the starting city node O for goods, followed by the next gene Xi, which represents the random selection of other city nodes for connection through a certain transportation method from the starting

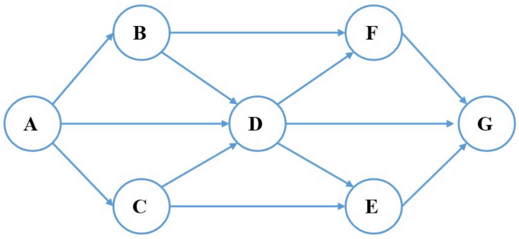

Fig. 3.2: Transportation Network Diagram

city node. The i on gene Xi represents the transportation method used for goods transportation between city node O and city node X, it is randomly selected from the existing transportation modes between these two city nodes, and then the process of random selection is repeated until reaching the destination node D, thus forming the first chromosome in the population.

Determine the initial group. Continuously repeating the above random selection process can generate the initial population required for genetic algorithm solving. The selection of the initial group should have a wide range of representativeness. Generally speaking, the group size should be between 10 and 100, which not only ensures computational efficiency but also enables the algorithm to converge to the global optimum.

Adaptation function. In genetic algorithms, fitness functions are used to indicate the superiority or inferiority of individuals and solutions. Different individuals have different fitness values, and individuals with higher fitness values have a higher probability of inheriting to the next generation. The author uses the minimum generalized transportation cost as the main evaluation criterion based on the characteristics of the problem. Therefore, for the author's multimodal transportation path optimization model, we mainly adopt the reciprocal of the total cost generated throughout the entire process of each transportation scheme as the individual fitness function.

Crossover and variation. Based on the crossover and mutation probabilities of genetic algorithms, individuals are subjected to crossover and mutation operations, and several sets of solutions are output. Chromosomes are randomly selected for partial gene exchange according to the crossover rate to achieve the process of chromosome crossover. The crossover rate is typically set between 0.25 and 0.75. The mutation rate represents the ratio of mutated genes to the total number of genes across all chromosomes, generally ranging from 0.0001 to 0.1.

Algorithm terminated. In the process of solving the optimal solution for the multimodal transportation path optimization model, after n generations of population reproduction, when the fitness function value tends to stabilize, that is, when the fitness function converges, the algorithm terminates [20].

3.6. Example Analysis. 30 tons of goods suitable for multimodal transportation will be transported from city A to city G. There are a total of five transit cities to choose from: B, C, D, E, and F. During the distribution process, there are at least one or more transportation modes to choose from, including road, railway, water, and air transportation. The transportation network diagram is shown in the following Figure 3.2.

The specific transportation options available between cities are described in Table 3.1.

4. Results and Discussion. The unit transportation costs and transportation times of various modes of transportation between cities are shown in Table 4.1. If a particular mode of transportation is unavailable in a city, its associated cost and time are treated as infinite. The unit transit costs between various transportation modes are detailed in Table 4.1, while the conversion times between different transportation modes at each node city are provided in Table 4.2.

Note: a/b/-, a represents the unit transportation cost (yuan/ton/hour), b represents the transportation time (hours), - represents the absence of a certain transportation method.

Other data includes total transportation time requirements and penalty costs incurred. The author sets the transportation time as 3 days (72 hours) and the penalty cost as 200 yuan per hour for overdue.

Table 3.1: Transportation modes between cities

	A	B	C	D	E	F	G
A	\	Public/Iron	Public/Iron	Public/Iron	\	\	\
B	Public/Iron	Public/Iron	Public/Water	Public/Iron	Public	\	
C	Public/Iron	Public/Iron	\	Public/Iron	Public/Iron	Public/Iron	\
D	Public/Iron	Public/Water	Public/Iron	\	Public/Water	Public/Iron	Public/Iron/ Water/Aviation
E	\	Public/Iron	Public/Iron	Public/Water	\	Public/Iron	Public/Water
F	\	Public	Public/Iron	Public/Iron	Public/Iron	\	Public/Iron
G	\	\	\	Public/Iron/ Water/Aviation	Public/Water	Public/Iron	\

Table 4.1: Unit transportation costs (yuan/ton/hour) and transportation time (hours) for various transportation modes between cities

	A-B	A-C	A-D	B-D	C-D	D-E	D-F	D-G	E-G	F-G
road transport	27/6	29/6	34/19	26/9	30/11	34/10	29/12	37/17	27/12	31/13
railway transportation	22/7	19/7	31/23	20/11	29/15	-	30/13	31/18	31/13	32/14
Waterway transportation	-	-	-	-	-	14/19	-	-	17/29	-
transport aviation	-	-	-	-	-	-	-	300/2	-	-

Table 4.2: Unit Transfer Costs (yuan/ton · hour)/Conversion Time (hours) between Different Transportation Modes

intercity	road transport	railway transportation	Waterway transportation	transport aviation
road transport	0/0	31/2	24/2	24/2
railway transportation	19/2	0/0	24/1	24/2
Waterway transportation	21/1	22/1	0/0	22/1
transport aviation	24/2	24/1	22/1	0/0

The network is addressed using a genetic algorithm implemented in MATLAB. The algorithm is configured with the following parameters: an initial population of 90 individuals, a crossover probability of 0.6, and a mutation probability of 0.01. After 100 iterations, it was found that the fitness change between adjacent generations was less than 0.01, indicating that the population mean of the running results had stabilized. At this point, the results can be considered converged, as shown in Figure 4.1.

The final optimized route obtained is: A → Railway → B → Highway → D → Waterway → E → Highway → G, with a total cost of 37710 yuan, transportation cost of 32340 yuan, transit cost of 5370 yuan, and a total time of 59 hours, including 8 hours of transit time and 3 transit times, without incurring any penalty costs.

If the author adopts a single transportation method, the optimal solution obtained is railway transportation: A-D-G, with a total cost of 41280 yuan and a total time of 38 hours.

5. Conclusion. The author proposes a coal transportation multimodal transport path selection based on genetic algorithm. In response to the logistics distribution problem of multimodal transport, the author constructs a multi-objective optimization model with the minimum cost of transportation mode usage cost, cargo transportation transit cost, transportation time cost of goods in transit, and cargo transit time cost, which is theoretically feasible Analyze the applicability of genetic algorithms and design a genetic algorithm for multimodal logistics distribution. The calculation results of the example show that using genetic algorithm can reliably find better solutions in logistics distribution optimization problems There are many factors that affect the logistics and distribution of multimodal transport, and this study selects the main factors that affect

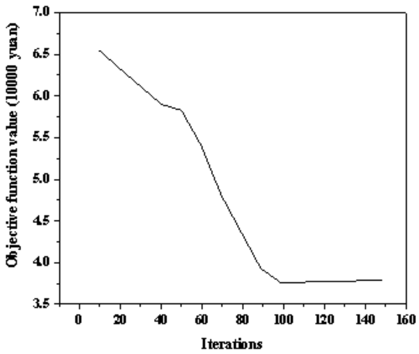

Fig. 4.1: Evolution of Optimal Solution

logistics and transportation distribution. Other factors such as driver labor costs, vehicle maintenance and upkeep costs, etc. are not fully covered; Moreover, some conditions assumed during modeling and algorithm design may differ from the actual operating environment. Therefore, how to more accurately transform the actual multimodal logistics distribution problem into an accurate model and make theoretical research more meaningful is a further direction for deepening.

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